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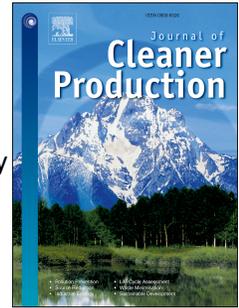
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The role of Big Data in explaining disaster resilience in supply chains for sustainability

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The role of Big Data in explaining disaster resilience in supply chains for sustainability

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Abstract

The purpose of this paper is to propose and test a theoretical framework to explain resilience in supply chain networks for sustainability using unstructured Big Data, based upon 36,422 items gathered in the form of tweets, news, Facebook, WordPress, Instagram, Google+, and YouTube, and structured data, via responses from 205 managers involved in disaster relief activities in the aftermath of Nepal earthquake in 2015. The paper uses Big Data analysis, followed by a survey which was analyzed using content analysis and confirmatory factor analysis (CFA). The results of the analysis suggest that swift trust, information sharing and public-private partnership are critical enablers of resilience in supply chain networks. The current study used cross-sectional data. However the hypotheses of the study can be tested using longitudinal data to attempt to establish causality. The article advances the literature on resilience in disaster supply chain networks for sustainability in that (i) it suggests the use of Big Data analysis to propose and test particular frameworks in the context of resilient supply chains that enable sustainability; (ii) it argues that swift trust, public private partnerships, and quality information sharing link to resilience in supply chain networks; and (iii) it uses the context of Nepal, at the moment of the disaster relief activities to provide contemporaneous perceptions of the phenomenon as it takes place.

Keywords: Resilience, Big Data, Sustainability, Disaster, Exploratory Factor Analysis, Confirmatory Factor Analysis.

1. Introduction

Climate change has been at the forefront of interest for both academics and practitioners. McGuire (2012) noted that a changing climate not only causes floods, droughts, and heatwaves, but can also bring erupting volcanoes and catastrophic earthquakes, that is, natural disasters. As natural disasters get stronger they bring human losses (death, injury, and permanent displacement) that often exceed the economic toll (Cutter, 2013). Unfortunately, current disaster policies are reactive with a short-term focus. They aim at responding to a natural disaster to restore the community back to normality. However, literature (Cutter, 2013) suggests that investments in long-term disaster resilience plans are needed that strengthen the ability of communities to prepare and plan for, absorb, respond to, and recover from present and future disasters is a vital step towards sustainability.

In recent years we have seen increasing climate change literature focussing on the intersection between climate change adaptation and disaster risk reduction, and poverty and development as 'climate resilient development'. Bahadur et al. (2010) have argued that despite this growth in popularity, there has been little attempt to scrutinise the literature to examine how it might underpin an operational approach to resilience. Cannon and Muller-Mahn (2010) have argued that adaptation to climate change is the pressing need; however at the same time it poses a threat to the prospects of development in poor countries. The concept of resilience in supply chain networks has become one of the most debated subjects among scholars in operations and supply chain field (see, Christopher and Peck, 2004; Sheffi and Rice, 2005;

Ponomarov and Holcomb, 2009; Bhamra et al. 2011; Hassler and Kohler, 2014; Soni et al. 2014; Mari et al. 2014; Novocorti et al. 2015; Rajesh and Ravi, 2015; Du et al., 2016). According to Rochas et al. (2015), resilience depends on the type of system to be analysed and the methodology applied (i.e. quantitative or qualitative evaluations). Scholars (see Tobin, 1999; Cutter et al., 2008; Magis, 2010; Cutter, 2013) have illustrated the link between resilience and sustainability. Tobin (1999) in particular has suggested that “sustainable and resilient communities are defined as societies which are structurally organized to minimize the effects of disasters, and, at the same time, have the ability to recover quickly by restoring the socio-economic vitality of the community” (p. 13). We can argue based on extensive literature review that operationalization of resilience thinking is founded upon the understanding that ecological and social systems are highly integrated. Based on extensive discussions we believe that there is pressing need for a comprehensive approach for tackling a changing climate by making socio-ecological systems (SESs) more resilient to ‘disturbances’ and, be it hydro-meteorological disasters, change in rainfall patterns/quantity or temperature variability, it is projected that climate change is likely to change the nature, and increase the intensity and frequency, of disturbances that SESs will face across the globe.

Day et al. (2012) highlighted the need to attend to the complex attributes of supply chain networks in order to manage the increasing number of disasters that disrupt commerce and community life around the world. In support of this, Hazen et al. (2014) have argued that supply chain professionals need to find new ways of thinking about how data on disasters are produced, organized, stored, and analysed. In this context, the evolving field of ‘Big Data’ shows great potential for optimizing recovery strategies and managing supply chain networks.

Big Data, defined as “as a holistic approach to manage, process and analyze the “5 Vs” (i.e., volume, variety, velocity, veracity and value) in order to create actionable insights for sustained value delivery, measuring performance and establishing competitive advantages” (Wamba et al. 2015, p. 235) has emerged as both a strategic and operational tool that may bring fundamental changes to supply chain and humanitarian supply chain management (Brown et al., 2011; Chen et al., 2012). ‘Big data and business analytics’ is one of the fastest evolving fields due to the convergence of Internet of Things (IOT), and cloud and smart assets (Bughin et al. 2010).

So far, within the supply chain literature (see, Waller and Fawcett, 2013) and resilient supply chain literature (see, Blackhurst et al. 2011; Soni et al. 2014) scholars have used *structured data* to identify and test the enablers of resilience in supply chains because of limitations of volume and variety of available data. In this paper, however, we focus on *unstructured data* as a form of Big Data that constitutes over 80% of the total volume of organizational data. No matter if studies have looked into how people use social media to respond to disasters and how appropriate measures are taken to enable recovery (see Chae et al., 2014; Shelton et al., 2014; Burns, 2015; Chae, 2015), there are yet studies to be conducted that look into the analysis of unstructured data to explain disaster resilience for sustainability. Furthermore, despite the popularity of Big Data there is a lack of clarity in term of its understanding and applications in the supply chain networks (Wamba et al. 2015; Song et al., 2016). To address these gaps, our research questions are as follows:

- (1) *What is the role of Big Data (unstructured data) within supply chain networks?*
- (2) *How could unstructured data in supply chain networks be exploited to explain disaster resilience for sustainability?*

To answer our research questions, firstly we conducted a literature review on the role of Big Data within supply chain networks, and subsequently a Big Data analysis of 36,422 items gathered in the form of tweets, news, Facebook,

WordPress, Instagram, Google+, and YouTube (unstructured data). We applied Chae's (2015) proposed framework for our study guided by ethical principles. Our review of literature and unstructured data analysis revealed our framework which attempts to explain resilience in supply chain networks. Our framework was then tested using data from 205 responses by relief workers, officials, and local people who were involved in disaster relief operations after the Nepal earthquake in April 2015. Our study offers two main contributions to the Big Data and supply chain networks literature: (i) We argue that Big Data analysis can be used in explaining the enablers of resilience in supply chain networks; (ii) We propose swift trust, public private partnerships, and quality information sharing as enablers of resilience in supply chain networks for sustainability.

The rest of the paper is organized as follows. In the next section we review the literature on resilience and supply chains. It follows the analysis of the unstructured data by analyzing over 36,422 tweets related to Nepal earthquake and the development of our theoretical framework. Following construct operationalization, description of data collection and analysis methods; we test our framework and present the results. It follows a discussion of the findings and their theoretical and managerial implications. The paper concludes with a summary of our findings, limitations, and directions for future research.

2. Resilience and supply chains

Sheffi and Rice (2005) defined supply chain resilience as the property of a supply chain network that enables it to regain its original configuration soon after disruption from earthquakes, floods, hurricanes and tropical storms, tornadoes, tsunamis, and diseases. Bhamra et al. (2011) provided an overview of resilience as a term used in various contexts in management literature. Burnard and Bhamra (2011) developed a conceptual framework for organizational resilience and offered further research directions.

Soon after a disaster, resilience in the supply chain will determine the path to normality through collaboration among the various actors in the supply chain network (Boin et al., 2010; World Economic Forum, 2013; Ivanov et al., 2014). Recently Zobel (2011) and Zobel and Khansa (2014) have defined disaster resilience and provided a quantitative model to assess resilience in the supply chain. Tierney and Bruneau (2007) and Bruneau et al., (2003) proposed "The Resilience Triangle", which helps to analyze how various supply chain strategies can reduce the size of the supply chain triangle. To investigate the resilience triangle concept, we briefly reviewed some of the existing literature (Bruneau et al., 2003; Tierney and Bruneau, 2007; Zobel, 2011).

To measure loss of resilience, Bruneau et al. (2003) introduced a mathematical equation to determine the loss of resilience as:

$$R = \int_{t_0}^t [100 - Q(t)] dt$$

Where R = loss of resilience and $Q(t)$ = quality of infrastructure as a function of time, $Q(t)$ to T (time) $\rightarrow t$

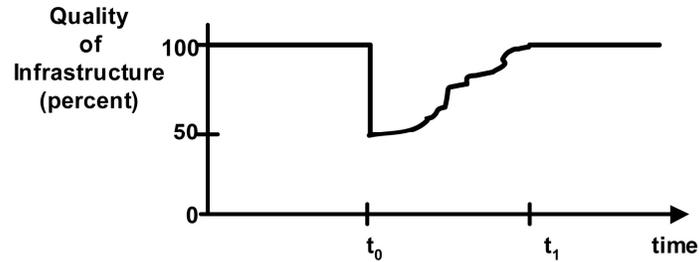


Figure 1: Resilience Triangle (Adapted from Bruneau et al., 2003)

When disaster strikes, the quality of the infrastructure decreases, as shown by the vertical line, and then is gradually restored to normality as time passes, as in Figure 1. Bruneau et al. (2003) argued that in order to improve rapidity, the height of the triangle should be smaller [i.e. $(t_0-t) \rightarrow 0$], or, in order to reduce the depth, the resistance property in the supply chain network needs to be built. This is termed robustness and is one of the desired dimensions of resilience. In other words, an attempt needs to be made to decrease the area measured by the triangle. This has been used in recent years to measure the resilience of physical infrastructure elements such as hospitals (Zobel, 2011). In our research, we further use the modified TOSE resilience framework of Tierney and Bruneau (2007), which pays attention to Technical domain, Organizational resilience, Societal perspective and Economic resilience. Day (2014) attempted to explain the resilience property in a supply chain using complexity theory and a systems resilience approach. Day (2014) identified three key elements in any resilient supply chain: (i) topology (path lengths, redundancies, clustering, etc.); (ii) entities (non-governmental organizations, military, third party logistics providers, government agencies, military, donors, media etc.) and (iii) environment. Stewart et al. (2009) suggested that to build community resilience, public-private partnerships need to be effectively leveraged to build community resilience. Key to this purpose is supply chain resilience and critical infrastructure/ key resource resilience. The World Economic Forum (2015) has identified the need for public-private initiatives to build resilience in Nepal to help in building resilience into housing, ensuring safe schools, and enabling tourism. Sudmeier et al. (2013) have proposed a resilience framework in the Nepalese context, which is highly prone to disasters resulting from rapid change in climate, urbanization and mountainous region. They have identified four constructs that is, economic, social, human resources, natural resources, and physical resources. One conclusion from the literature could be that supply chains (and other infrastructure) that is more resilient is likely to be less seriously affected by a disaster, and will be able to recover more quickly.

2.1 Big Data within supply chain networks for sustainability

In recent years, mainly due to the advancements in the use of technology (e.g. cloud computing, smart mobile devices), large amounts of data, mainly unstructured, have been accumulated. Big data has the potential to transform business processes (Chen et al., 2012; Wamba et al., 2015; Song et al., 2016) as it does not only concern finance or manufacturing and service operations, but spans all aspects of our lives (Zhou et al., 2016). Big Data has particular properties referred to as volume (referring to the amount of data), velocity (referring to frequency or speed by which data is generated and delivered), veracity (referring to data quality) and value (referring to the benefits from the analysis and use of big data) (Dubey et al., 2015; Wamba et al., 2015; Song et al., 2016). Within operations and supply chain management, Big Data has the potential to bring improved productivity, competitiveness and efficiency, as well as to help in decision making

with regard to pricing, optimization, operational risk reduction and improved product and service delivery (ibid). In improving sustainable societal development and building resilient disaster infrastructure and capabilities - that is sustainability and resilience - big data can help “scientists, policy makers and city planners develop policies, strategies, procedures and practices that will internalize currently externalized environmental and human health costs on society (Song et al. 2011; Song et al. 2015a). This will help governments and societies to make more effective local, regional, national and global progress toward truly sustainable societies.” (Song et al. 2012; Song et al., 2015: p. 2). Big data can hence assist data scientists and policy makers in (i) developing and implementing policies and strategies that protect and manage natural resources in an environmental way; (ii) preventing wastage of resources and degradation of capacities that can provide essential services for human health and sustainable development of society (iii) limiting the production of pollutants by converting them into useful products (Song et al., 2015); (iv) developing appropriate environmental protection policies and frameworks (Song et al., 2014a; 2015); and (v) looking into disaster management and analyzing how people respond to disasters in order to take appropriate measures and devise policies that will enable recovery and restoring back to normality for communities (e.g. Chae et al., 2014; Shelton et al., 2014; Burns, 2015).

Big Data can help in both alleviating and recovering from the negative consequences of disasters, as well as in building social and natural capital and enhancing adaptive capability to cope with the future (Folke et al., 2010; Redman, 2014). However, scholarly work has been limited in presenting future benefits and conceptualizations of the role of Big Data for sustainability and resilience, and more importantly, although there are studies looking at Big Data and disaster management (Chae et al., 2014; Shelton et al., 2014), there have been no studies that utilize Big Data (unstructured data) to explain disaster resilience for sustainability. To address this gap, in the next section we present our results of the unstructured (Big Data) analysis, which, together with our literature review resulted in our proposed framework, which is tested using structured data from a survey conducted in Nepal.

3. Unstructured Data Analysis

To begin, we performed descriptive analytics. The first step in this analysis was to collate a large dataset of terms related to the distribution of aid and reconstruction phase in Nepal, across social and mainstream news media for the period 15th May to 19th June 2015. This search yielded a little over 36,422 items. The breakdown of the tweets based on their sources is presented in Table 1. To ensure that our work done is supported by ethical-use principles, we followed the guidelines of Rivers and Lewis (2014). The guidelines include: 1) study designs using Twitter-derived data is transparent and readily available to the public. 2) we respect the tweet sent in any context. 3) all data that could be used to identify tweet authors, including geolocations, has been secured. 4) no information collected from Twitter should be used to procure more data about tweet authors from other sources. 5) we respect user’s attempt to control his or her data by respecting privacy settings. As researchers, we believe that a discourse within the research community is needed to ensure protection of research subjects.

Table 1: Distribution of data collected from various sources

| Content Type | Count | Percentage |
|------------------|-------|------------|
| Tweets (Twitter) | 29720 | 81.60 |

| | | |
|------------------|------|------|
| News | 1200 | 3.29 |
| Facebook | 3400 | 9.34 |
| WordPress | 120 | 0.33 |
| Instagram | 178 | 0.49 |
| Google+ | 118 | 0.32 |
| YouTube | 1686 | 4.63 |

During the analysis of the data we identified two threads. The first relates to how real-world events can be detected using such datasets, and the second looks at whether there is any useful information that could help to discover people needed help in the aftermath of the earthquake. The descriptive analytics followed by content analysis of the tweets. The most popular keywords related to disaster relief activities from our analysis are presented in Table 2. These issues are also noted in the literature (see, Altay 2008; Altay et al. 2009; Kovacs and Spens 2009; L’Hermitte et al. 2014).

Table 2: Issues Related to Disaster Relief Activities

| Barriers | Explanation |
|--|--|
| Confusion | Confusion due to poor alignment among humanitarian actors coming from different countries. |
| Obstruction | Lack of understanding of local culture among disaster relief workers. |
| Old Clothes | Damaged dignity of survivors due to donations of old clothes. One of the tweet messages read: “we are not beggars...” |
| Expired Food | Expired food that could be consumed. The majority refused to accept such packages. |
| Lack of ownership | Imported medicine, food, clothes and other relief materials lying in warehouses for over 10 days but due to lack of ownership the materials were not delivered. |
| Acute fuel shortage | Due to political reasons fuel supplies were delayed for more than three weeks, thereby delaying relief activities. |
| Logistics challenges due to few entry points | Due to few entry points the movements of trucks transporting relief materials to major hubs were delayed. |
| Landslides after earthquakes | Landslides impacted on the movement of the trucks and other vehicles transporting relief materials from warehouses to various affected places. Roads connecting the warehouses and disaster affected places were completely destroyed. |
| Monsoon season | The temporary settlements were not adequate to protect the victims |

| | |
|--|---|
| | from the heavy rainfall; also the transport of relief materials was made difficult. |
|--|---|

Table 3 shows the areas which emerged from the unstructured data as priorities for building resilience.

Table 3: Top priorities for building resilience

| Priorities | Explanation |
|-----------------------|--|
| Ensuring Safe Schools | The school buildings were completely destroyed. Over 75000 schools going children's were affected in the region of Gorkha. |
| Building Hospitals | Hospitals were destroyed. Health security is one of the major concerns. |
| Building Houses | Over 75% of the total population was displaced. Temporary shelters were not enough to protect against extreme weather conditions (monsoon and winter). Inappropriate building materials were used to build shelters. |
| Roads | Due to earthquake and landslides most of the connecting roads were completely destroyed, affecting disaster relief activities. |
| Resuming Tourism | Tourism is valued as the major contributor to a sustainable Nepal economy. The country is an attractive, safe, exciting and unique destination through conservation and promotion, leading to equitable distribution of tourism benefits and greater harmony in society. |

4. Research Methods

We conducted qualitative content analysis to identify the constructs for building disaster resilience. Consistent with the call for innovative sources of data and prior environmental and operations management literature (Tate et al. 2010; Chan et al. 2015), a qualitative content analysis is a useful method to identify disaster resilience antecedents for sustainability in real life practices from accessible documents and communication materials (Boyer and Swink, 2008). This approach has helped us to overcome the limitations of literature review and in-depth interviews with experts by improving the generalizability of the measurement scales (Chan et al. 2015). Tangpong (2011) argued in his research that content analysis may be questioned for its validity as the information gathered from public sources. In our case we analyzed using tweets and other kinds of messages hence guided by Jick's (1979) suggestions we have attempted to lower the risk of content analysis by using it in tandem with survey research. Therefore, a large-scale quantitative research was conducted subsequently for primary data collection to statistically validate our constructs (see Figure 1). The use of unstructured data and structured data is useful to improve the rigor by allowing triangulations and to overcome bias issues that may incur with the use of single research (Boyer and Swink, 2008). In the next section we discuss our theoretical framework and its empirical validation.

4.1 Theoretical Framework

Our theoretical framework, shown in Figure 2, is grounded in both our literature review and the unstructured data analysis. The framework comprises seven elements: public-private partnership, ‘swift trust’ (Tatham and Kovacs, 2010), ‘quality information sharing’ (Altay and Pal, 2014), supply chain resilience, critical infrastructure resilience, ‘community resilience’ (Stewart et al., 2009), and ‘resources resilience’ (Sudmeier et al., 2013). Our framework is inspired by the TOSE framework. Each of the elements of our framework corresponds to particular dimensions of the TOSE framework and particular priorities from Table 3, as presented in Table 4.

Table 4: Correspondence of priorities to the TOSE framework dimensions and to the elements of our proposed framework

| Dimensions of TOSE framework (Tierney & Bruneau, 2007) | Priorities identified | Elements of our proposed framework |
|---|---|---|
| Technical: Refers to the ability of the physical infrastructure to perform adequately in the case of a natural disaster. | Ensuring Safe Schools Building Hospitals Building Houses Roads | Public-private partnership Quality information sharing Resources resilience Supply chain resilience |
| Organizational: Refers to the ability of organizations to achieve post-disaster resilience. | Building cooperation among members Building leadership Training Information management | Public-private partnership Quality information sharing Resources resilience Supply chain resilience Swift trust |
| Social: Refers to the measures taken to relieve affected communities from the negative consequences of a disaster due to the loss of critical services. | Resuming education for children’s Improving health system infrastructure Resuming Tourism | Community Resilience Critical infrastructure resilience Public-private partnership Swift trust Quality information sharing Supply chain resilience |
| Economic: Refers to the ability to reduce direct and indirect economic consequences of a natural disaster. | Improving transportation Resuming Tourism | Community Resilience Critical infrastructure resilience Public-private partnership Swift trust Quality information sharing Supply chain resilience |

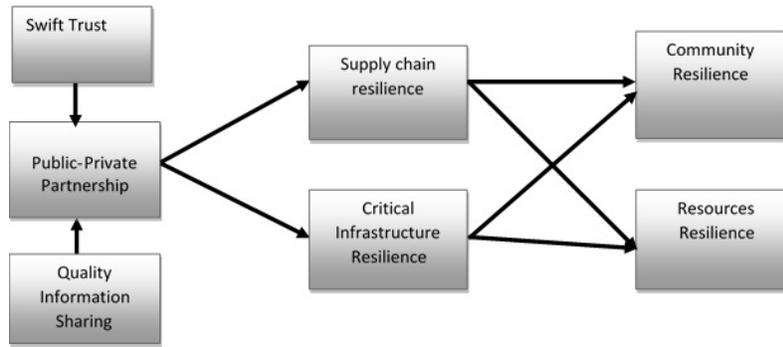


Figure 2: Resilience in Supply Chain Networks

Public-Private Partnership

Stewart et al. (2009) have underlined the growing role of private organizations in helping disaster-affected victims. Horwitz (2008) suggested that private players played a significant role in the response to the Hurricane Katrina disaster compared to their government players. Tomasini and Van Wassenhove (2009) argued that private organizations help in disaster relief by providing cash, goods, human resources, knowledge and expertise. Tomasini and Van Wassenhove (2009) have further argued that in recent years private companies are increasingly opting to design their social engagement through long-term partnership with humanitarian partners. It is noted that commercial logistics companies participate in partnerships with humanitarian organizations, approaching the latter not only from a charitable concern but also as opportunity for learning and developing their businesses. Humanitarian agencies invest equal resources, hoping to enhance their performance and core competencies through interaction with their private sector partners. These agencies can mainly benefit from their partners in two areas: back-office support for better disaster preparation and movement of key assets during a crisis (e.g., food donations, medication, shelters, or telecommunications equipment). Chen et al. (2013) have further argued that countries around the world are adopting policies that emphasize the importance of partnerships for disaster resilience. The World Economic Forum (2015) has highlighted the role of partnerships for building resilience in Nepal. Hence, based on the literature and unstructured data analysis, we argue that public-private partnership can play a significant role in building supply chain resilience and critical infrastructure resilience.

Supply Chain Resilience

Supply chain resilience has attracted significant attention from both academics and practitioners due to increasing uncertainty resulting from rapid climate change, rapid urbanization and political instability. Christopher and Peck (2004) have focused on supply chain engineering, supply chain collaboration, agility and building supply chain risk culture to build resilient supply chain networks. Sheffi and Rice (2005) have further noted that focusing on building redundancy, flexibility and changing culture will help build resilient supply chain networks. Pettit et al. (2013) have further noted that

resilience in supply chain networks is a key property during disasters that can be accessed by vulnerabilities and capabilities. Wieland and Wallenburg (2013) noted how relational competencies such as communication, co-operation and integration can play a significant role in building resilience in supply chain networks. Stewart et al. (2009) illustrated that supply resilience can play significant role in building community resilience. Hence, based on our literature review and unstructured data analysis we propose that supply chain resilience could help build community resilience and resources resilience.

Critical Infrastructure Resilience

Stewart et al. (2009) noted that building critical infrastructure resilience is pivotal for building community resilience. In our study we adopt the definition from Stewart et al. (2009) “...critical infrastructure includes the assets, systems and networks [] so vital to any nations that their destruction would have debilitating effect on security, national economic security, public health or safety, or any combination thereof. Key resources are publicly or privately controlled resources are essential to the minimal operations of the economy and governance...” (p. 349). Our extensive review indicates that building schools, hospitals, road, buildings and other critical infrastructure that support both social and economic development are immediate concerns. The World Economic Forum (2015) has identified other immediate requirements including building safe schools and houses for affected people who are provided with temporary settlements that are not enough to protect against extreme climate such as monsoon and winters. Sudmeier et al. (2013) have noted that Nepal is highly prone to disasters such as floods, landslides and earthquake. To sustain economic and social development in Nepal, there is a dire need for disaster resilient buildings and roads. Hence based on our literature and data analysis we suggest that critical infrastructure plays a significant role in building community resilience and resources resilience.

Community Resilience

Stewart et al. (2009) have argued that community resilience may be regarded as a sub-set of national resilience. Response to disasters begins at the local level and must become a local/state level event before using the resources of the federal government (Kapucu, 2008; Stewart et al. 2009). Community resilience is completely integrated within economic and social systems. Community resilience encompasses a broader domain that includes the resilience of relevant stakeholders who operate within its economic and social systems (Stewart et al. 2009).

Resources Resilience

Sudmeier et al. (2013) have noted the importance of natural resources resilience to achieve sustainable development in risk-prone regions such as Nepal due to floods, landslides and earthquakes. In this research resources were further classified into human resources, natural resources and physical resources.

Swift Trust

Tatham and Kovacs (2010) have argued that swift trust plays a significant role in improving coordination among humanitarian actors. They have identified five characteristics of swift trust as follows: (i) Information regarding actors

involved in disaster relief activities; (ii) dispositional trust; (iii) the clear rule for classification of processes and procedures; (iv) role clarity; and (v) category (i.e. gender, ethnicity).

Quality Information Sharing

Information sharing has significant impact on supply chain performance (see, Yu et al. 2001; Kwon and Suh, 2004; Li and Lin, 2006). Balcik et al. (2010) argue that coordination among humanitarian supply chain actors refer to, for instance, resource and information sharing, centralized decision making, conducting joint projects, regional division of tasks, or a cluster-based system in which each cluster represents a different sector area (e.g., food, water and sanitation, and information technology). Altay and Pal (2014) have further stressed the importance of quality of information sharing for building coordination among agents in humanitarian supply chain networks. Hence, we argue that quality information sharing among public and private partners can help strengthen cooperation, which may result into an efficient and effective partnership.

4.2 Research Design

4.2.1 Construct Operationalization

To further validate our theoretical framework (Figure 2), we collected structured data using a survey. The survey instrument was developed by identifying appropriate measurements (scales) from the literature. These scales were modified to be made more suitable in the context of supply chain networks. The target respondents were those relief workers and local people who were involved in disaster relief operations in Nepal earthquake disaster. The Nepal officials and a panel of experts having several years of expertise related to disaster relief operations in the Himalayan region examined the face validity of the questions. All the exogenous constructs in the model were operationalized as reflective constructs. The dependent constructs, community resilience and resources resilience, were operationalized as formative constructs as discussed next.

Public-Private partnership

Following Stewart et al. (2009) we identified the following measures for public-private partnership: (i) the quality of information exchange between the partners; (ii) the degree to which a firm adapts to the situation and manages disaster consequences through collaboration with local, state, and federal government agencies; (iii) the level of transparency related to relief materials' movement and utilization of resources gathered through donations; (iv) the degree of respect that between the partners.

Supply Chain Resilience

We drew on Bruneau et al. (2003), Christopher and Peck (2004) and Sheffi and Rice (2005) to create a five-item reflective scale. Supply chain resilience refers to the extent to which: redundancy is built in the supply chain network;

flexibility is built in the supply chain network; supply chain actors collaborate in the supply chain network; supply chain risk culture is built; and speed with which normality is achieved.

Critical Infrastructure Resilience

This was adapted from Stewart et al. (2009) and World Economic Forum (2015) as a five item reflective scale. It refers to the extent to which: disaster resilient school buildings can be constructed immediately, disaster resilient hospital buildings can be constructed immediately, disaster resilient bridges can be constructed immediately, disaster resilient houses can be constructed immediately to provide shelter to displaced people, and disaster resilient roads can be constructed immediately to resume efficient and effective movement of goods and related services.

Community Resilience

This was adapted from Stewart et al. (2009) and Norris et al. (2008). It refers to the extent to which social resilience and economic resilience can be built within a supply chain network. Social resilience relates to the creation of organic capabilities to sense, evaluate, and adapt to post-disaster consequences by community. To measure social resilience we identified three items: information and communication, community competence and social capital. To measure economic resilience we used three items, that is, microeconomic, mesoeconomic and macroeconomic. Stewart et al. (2009) have explained the term 'microeconomic' as individual behaviour of firms, households, or organizations. 'Mesoeconomic' refers to individual market or cooperative group, whereas 'macroeconomic' refers to all individual units and markets combined, though the whole is not simply the sum of its parts, due to interactive effects of an economy.

Resources Resilience

Resources resilience involves planning, organization of restoration and other processes, where high level efficiency in the use of both materials and time resources is required. This element was adapted from Sudmeier et al. (2013) as a three item construct that includes human, natural and physical resources.

Swift Trust

Tatham and Kovacs (2010) have argued that swift trust has a positive impact on building coordination among humanitarian supply chain actors. In our study we have reviewed the relevant literature (Hung et al. 2004; Tatham and Kovacs, 2010) and have used five items to measure swift trust: (i) Information regarding actors involved in disaster relief activities; (ii) dispositional trust; (iii) the clear rule for classification of processes and procedures; (iv) role clarity; and (v) category (i.e. gender, ethnicity etc.).

Quality Information Sharing

Balcik et al. (2010) argue that coordination among humanitarian supply chain actors refers to resource and information sharing, centralized decision making, conducting joint projects, regional division of tasks, or a cluster-based system in

which each cluster represents a different sector area (e.g., food, water and sanitation, and information technology). Additionally, we attempted to modify the construct by Hsu et al. (2008) and used three items to measure quality information sharing: (i) use of compatible information systems with various actors engaged in disaster relief activities; (ii) sharing of information related to various resources deployed for relief activities (i.e. relief materials, manpower, modes of transportation etc.); (iii) existence of a joint information center (JIC) for effective sharing of information among various agencies or organizations involved in a disaster relief project.

These items were measured on a five-point Likert scale with anchors ranging from strongly disagree (1) to strongly agree (5) in order to ensure high statistical variability among survey responses. Prior to data collection the survey instrument was pre-tested for content validity in two stages. In the first stage, three experienced researchers were asked to critique the questionnaire for ambiguity, clarity, and appropriateness of the items used to operationalize each construct (Chen et al. 2004; DeVellis, 2012). These researchers were also asked to assess the extent to which the indicators sufficiently address the subject area (Dillman, 1978). Based on the feedback received from the researchers we further re-worded the questions to enhance clarity and appropriateness of the measures purporting to tap the constructs. In the second stage the instrument was e-mailed to almost 30 supply chain managers affiliated with APICS. These executives were asked to review the questionnaire for structure, readability, ambiguity, and completeness. We further modified the instrument based on the experts' feedback.

4.2.2 Data Collection

To test our theoretical framework (see Figure 2) we gathered data using a structured questionnaire among the officers and managers who are involved in Nepal disaster relief operations. We have distributed 275 questionnaires with the help of the National Institute of Disaster Management (NIDM). The questionnaires were distributed randomly to the managers who are involved directly in disaster relief activities and who had had significant exposure to disaster relief and its related activities for several years as Nepal is prone to disasters resulting from flood, landslides or earthquake. We believe that the research design is suitable for this research in the light of the unique social and cultural context. In Nepal and India, government officials usually share their opinions or respond to questionnaires if they are approached through personal contact. With help of NIDM we managed to collect 205 usable responses (see Table 5 and Table 6), showing an effective response rate of 74.54%. We further assessed non-response bias using t-tests to compare the early respondents and late respondents response and found no-significant differences ($p > 0.05$).

Table 5: Types of participating organizations

| Types of Organization | | |
|--------------------------------------|----|-------------|
| | N | %(approx..) |
| Infrastructure Development Companies | 5 | 6 |
| Transporters | 25 | 30 |
| Warehousing | 15 | 18 |
| Army Logistics | 2 | 2 |
| Border Road Organization | 1 | 1 |
| NGOs | 10 | 12 |
| Medical Aid Agencies | 25 | 30 |

Table 6: Respondent Demographics

| Title | CEO or Equivalent | Vice Presidents | Senior Managers | Managers | |
|-------------|-------------------|-----------------|-----------------|----------|-----|
| N | 2 | 35 | 75 | 93 | 205 |
| %(approx..) | 1 | 17 | 37 | 45 | |

5. Structured Data Analyses and Results

Before we performed exploratory factor analysis (EFA) followed by confirmatory factor analysis (CFA), we tested the indicators for the assumption of constant variance, existence of outliers, and normality. We used plots of residuals by predicted values, rankits plot of residuals, and statistics of skewness and kurtosis (Curran et al. 1996; Cohen et al. 2003; Song et al. 2013; Dubey and Gunasekaran 2015). The maximum absolute values of skewness and kurtosis of the indicators in the remaining dataset were found to be 1.668 and 2.374, respectively. These values were well within the limits recommended by past research (Curran et al. 1996). Finally, we found that neither the plots nor the statistics indicated any significant deviance from the assumption.

We further tested unidimensionality following two conditions (Gerbing and Anderson, 1988). First, an item must be significantly associated with the empirical indicators of a construct and, second, it must be associated with one and only one construct (Chen et al. 2004). Unidimensionality was established in prior studies (see Bentler, 1986; Hair et al. 2006). Based on several fit indices ($\chi^2/df=1.69$; goodness of fit [GFI]=0.97; adjusted goodness of fit [AGFI]=0.91; Bentler comparative fit index[CFI]=0.97; root mean square residual [RMSR]=0.06; and root mean square error of approximation [RMSEA]=0.05), we can conclude that constructs exhibit unidimensionality.

Since our research framework contains both reflective and formative constructs, and we have relatively small sample size (see, Field 2005: for twenty nine indicators we should have minimum 282 responses) partial least square regression (PLSR) was chosen for data analysis (Chin et al. 2003). Fornell and Bookstein (1982) have argued that in general PLSR is better suited for explaining complex relationships as it avoids two problems: inadmissible solutions and factor indeterminacy.

We further performed EFA. We obtained seven parsimonious factors with each indicator loaded on respective factors (see Appendix A). To further test convergent and discriminant validity we used confirmatory factor analysis (CFA). Appendix B and Appendix C show that convergent and discriminant validity exists as suggested by Fornell and Larcker, (1981) and Chen and Paulraj (2004). Appendix B clearly shows the standardized factor loadings of each indicator (≥ 0.5), the composite reliability (SCR) (≥ 0.7) and average variance extracted (AVE) (≥ 0.5). The results clearly support the convergent validity test as suggested by scholars (see Fornell and Larcker 1981; Chen and Paulraj 2004; Fawcett et al.

2014). For discriminant validity we checked the squared root of AVE measured for each of the constructs, and it was found to be greater than the correlation coefficients between each pair of constructs in the same column. We also assessed common method bias as there is a high likelihood of potential biases resulting from multiple sources in case of self-reported data. Following the suggestions by Podsakoff and Organ (1986) we attempted to enforce a procedural remedy by asking participants not to answer questions purely on the basis of their own experience but to get this information from minutes of meetings. In addition we also performed statistical analyses to assess the severity of common method bias. Harmon one-factor test (Podsakoff and Organ, 1986) was conducted on seven constructs. Results showed that out of seven factors the most covariance is explained by one factor, namely critical infrastructure resilience (i.e. 19.14%). Hence we can conclude that common method biases are not likely to impact the study outcome.

6. Discussion

6.1 Theoretical Contributions

The potential use of unstructured data for explaining complex phenomena was ignored in the past due to limitations in exploring issues beyond the existing literature (see, Waller and Fawcett, 2013; Chae, 2015). The current trend is either to investigate theory using structured data (see, Blackhurst et al. 2011) or to develop mathematical models (Soni et al. 2014; Zobel and Khansa, 2014), or to use social media to study how people respond to disasters and how appropriate measures are taken to enable recovery (see Chae et al., 2014; Shelton et al., 2014; Burns, 2015; Chae, 2015). There have been no studies on the use of Big Data to explain disaster management for sustainability. In response to this gap, we formulated our framework based on both the relevant literature and the analysis of unstructured Big Data in the context of Nepal, in light of the earthquake that hit the area in April 2015. Drawing on our results, we argue for the use of unstructured Big Data analysis for the formulation of particular frameworks that aim to explain supply chain resilience and achieve sustainability. The uniqueness of our study is based on our use of Big Data in explaining the resilience in supply chain networks for sustainability, and our attempt to extend past literature that explains resilience in supply chain networks (see, Christopher and Peck 2004; Sheffi and Rice 2005; Stewart et al. 2009; Zobel and Khansa 2014).

Hence our findings extend the previous studies of Stewart et al. (2009) and Sudmeier et al. (2013) and suggest alternative factors enabling resilience in commercial supply chain networks (see, Christopher and Peck, 2004; Sheffi and Rice, 2005) using Tatham and Kovacs (2010) swift trust construct and Altay and Pal's (2014) quality information exchange theory. Furthermore, our study extends those works addressing the role of resilience in sustainability by looking at the role of Big Data in achieving resilience for sustainability. For instance, Burnard and Bhamra (2011) suggest that resilience enables companies to be sustainable by allowing them to be able to respond in a rapid and effective manner to threats and subsequently to mitigate them, and propose particular resilience models. However, they are not discussing the importance of making sense of Big Data and unstructured data analysis in building particular models for resilience and hence allowing for sustainability. In the same vein is the study by Pham and Thomas (2012) who link lean, agility, and sustainability for manufacturing resilience, but however they do not discuss the importance of Big Data in such attempts. Finally, our contribution lies also on the timely data collection, just at the aftermath of the catastrophe in Nepal. It is of

the first studies, if not the first, to the best of our knowledge, to assess the importance of particular factors at a time where teams are involved directly are exposed in disaster relief activities.

6.2 Managerial Implications

The current study offers guidance to managers who are engaged in the recovery phase after a disaster. The current study highlights swift trust, quality information sharing and public-private partnership as critical enablers for building resilience in supply chain network. The findings of our study are based upon the views of people who experienced the Nepal disaster of 2015, an earthquake followed by landslides. It is important for managers to attend to these factors enabling supply chain resilience, but also to note that these factors depend on the multifarious objectives, risks, and aims related to the particular disaster. Our framework provides particular enablers that need to be further tested and used by managers and could be related to particular key performance indicators (KPIs) and measures related to the performance of the supply chain during a particular disaster. Robust data collection and analysis, as well as investments in infrastructure and competencies are needed to put these KPIs and measures into practice, as well as to frequently audit them to ensure they are updated and adjusted. In this way learning about different enablers will be achieved, which is important in dealing with physical catastrophes and building a resilient supply chain. In such attempt, it is important that different stakeholders and managers are involved (Gunasekaran et al., 2015) and that such attempts take place right at the aftermath of an event, as in our study. We hence believe that the findings of our study can be used as guidance and could be adapted by disaster relief workers working in similar events occurring in different parts of the world.

7. Conclusions, Limitations and Further Research Directions

This paper investigated the use of Big Data in explaining resilience in supply chain networks for sustainability. Our paper employs Big Data to develop a theoretical framework on resilience in supply chain networks for sustainability. Our framework differs from other studies (e.g. Stewart et al., 2009) in that we look also at the role of swift trust and quality information sharing as enablers of resilience in supply chain networks, and that our framework is both based on literature and on the unstructured data analysis. Furthermore, we tested our framework through respondents who participated in the relief response. We, hence, argue that swift trust, public private partnership, and quality information sharing enable shaping supply chain resilience and critical infrastructure resilience, subsequently community resilience and resources resilience and hence resilience in a supply chain network. Drawing broadly on Big Data analysis and on the influence of swift trust, public-private partnership and quality information sharing we developed a theoretical framework that explains resilience for sustainability in supply chain networks. The framework was further validated using experts' opinion followed by CFA tests and a survey. The CFA test suggests that our constructs derived through content analysis possessed convergent validity and discriminant validity. The analyses were based on 36,422 tweets and 205 responses gathered from disaster relief workers. Our contribution, hence, lies in (i) illustrating the use of Big Data analysis in explaining resilience in supply chain networks for sustainability and formulate and test a framework in the context of resilient supply chains for sustainability. Swift trust, public private partnerships, and quality information sharing are important in shaping supply chain resilience and critical infrastructure resilience, subsequently community resilience and resources resilience and hence resilience in a supply chain network that may enable the achievement of

sustainability; and (iii) using the context of Nepal, especially at the moment when disaster relief activities take place to give us a more up-to-date perception of a phenomenon as it takes place.

While we believe that we have developed a framework and tested it using a reliable survey instrument and data, we also enumerate some limitations and unanswered questions. Firstly, we have used unstructured data and by performing sentiment analysis of the tweets gathered from various sources. However if we use advanced algorithms to perform sentiment analysis then we could further derive some more interesting dimensions that we may have missed in our current study. Secondly, the current study is limited to Nepal Earthquake aftermath. Hence our study can be further extended to other disasters due to flood, landslides and earthquakes in different contexts, or even compare and contrast relief supply chain network related factors between developing and developed countries, to better understand the role of other behavioral variables, such as the role of leadership and humanitarian culture. Thirdly, our study used cross-sectional data to validate our constructs. However in future if we can test the research hypotheses using longitudinal data collected over a period of time then we believe that causality can be established. Finally, we have noted that disasters occurring due to earthquakes, floods, landslides, hurricanes and heatwave are directly linked with rapid climate change. However to further establish causality there is need for Big Data research surrounding disaster resilience and sustainability.

Appendix A: Exploratory Factor Analysis Output

| | Public-Private Partnership | Supply Chain Resilience | Critical Infrastructure Resilience | Community Resilience | Resources Resilience | Swift Trust | Quality Information Sharing | |
|-------|----------------------------|-------------------------|------------------------------------|----------------------|----------------------|-------------|-----------------------------|--|
| PuP1 | | | | .959 | | | | |
| PuP2 | | | | .964 | | | | |
| PuP3 | | | | .914 | | | | |
| PuP4 | | | | .878 | | | | |
| ScRe1 | | | | | .865 | | | |
| ScRe2 | | | | | .844 | | | |
| ScRe3 | | | | | .824 | | | |
| ScRe5 | | | | | .798 | | | |
| ScRe6 | | | | | .839 | | | |
| CIRe1 | .962 | | | | | | | |
| CIRe2 | .966 | | | | | | | |
| CIRe3 | .959 | | | | | | | |
| CoRe1 | | | | | | | .956 | |
| CoRe2 | | | | | | | .900 | |
| CoRe3 | | | | | | | .873 | |
| ReRe1 | | .980 | | | | | | |
| ReRe2 | | .959 | | | | | | |
| ReRe3 | | .962 | | | | | | |
| ReRe4 | | .917 | | | | | | |
| ReRe5 | | .897 | | | | | | |

| | | | | | | | | |
|-----------|-------|-------|-------|-------|-------|-------|-------|-------|
| SwTr1 | | | .808 | | | | | |
| SwTr2 | | | .992 | | | | | |
| SwTr3 | | | .998 | | | | | |
| SwTr4 | | | .990 | | | | | |
| SwTr5 | | | .981 | | | | | |
| QIS1 | | | | | | .968 | | |
| QIS2 | | | | | | .920 | | |
| QIS3 | | | | | | .943 | | |
| | 2.78 | 4.45 | 4.57 | 3.46 | 3.48 | 2.67 | 2.49 | 23.90 |
| Variance% | 11.63 | 18.62 | 19.14 | 14.46 | 14.56 | 11.19 | 10.40 | |

Appendix B: Convergent Validity Test (Standardized Factor loadings, Scale Composite Reliability, Average Variance Extracted)

| Indicators | Standardized Factor Loadings | Variance | Error | Scale Composite Reliability | Average Variance Extracted |
|------------|------------------------------|----------|-------|-----------------------------|----------------------------|
| PuP1 | 0.959 | 0.92 | 0.08 | 0.96 | 0.86 |
| PuP2 | 0.964 | 0.93 | 0.07 | | |
| PuP3 | 0.914 | 0.84 | 0.16 | | |
| PuP4 | 0.878 | 0.77 | 0.23 | | |
| ScRe1 | 0.865 | 0.75 | 0.25 | 0.92 | 0.70 |
| ScRe2 | 0.844 | 0.71 | 0.29 | | |
| ScRe3 | 0.824 | 0.68 | 0.32 | | |
| ScRe4 | 0.798 | 0.64 | 0.36 | | |
| ScRe5 | 0.839 | 0.70 | 0.30 | | |
| CIRe1 | 0.962 | 0.93 | 0.07 | 0.97 | 0.93 |
| CIRe2 | 0.966 | 0.93 | 0.07 | | |
| CIRe3 | 0.959 | 0.92 | 0.08 | | |
| CoRe1 | 0.956 | 0.91 | 0.09 | 0.94 | 0.83 |
| CoRe2 | 0.9 | 0.81 | 0.19 | | |
| CoRe3 | 0.873 | 0.76 | 0.24 | | |
| ReRe1 | 0.98 | 0.96 | 0.04 | 0.98 | 0.89 |
| ReRe2 | 0.959 | 0.92 | 0.08 | | |
| ReRe3 | 0.962 | 0.93 | 0.07 | | |
| ReRe4 | 0.917 | 0.84 | 0.16 | | |
| ReRe5 | 0.897 | 0.80 | 0.20 | | |
| SwTr1 | 0.808 | 0.65 | 0.35 | 0.98 | 0.92 |
| SwTr2 | 0.992 | 0.98 | 0.02 | | |
| SwTr3 | 0.998 | 1.00 | 0.00 | | |
| SwTr4 | 0.99 | 0.98 | 0.02 | | |
| SwTr5 | 0.981 | 0.96 | 0.04 | | |
| QIS1 | 0.968 | 0.94 | 0.06 | 0.96 | 0.89 |
| QIS2 | 0.92 | 0.85 | 0.15 | | |
| QIS3 | 0.943 | 0.89 | 0.11 | | |

Appendix C: Discriminant Validity Test

| | PuP | ScRe | CIRe | CoRe | ReRe | SwTr | QIS |
|------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|
| PuP | 0.929 | | | | | | |
| ScRe | .237 | 0.834 | | | | | |
| CIRe | .217 | .105 | 0.962 | | | | |
| CoRe | .650 | .342 | .135 | 0.910 | | | |
| ReRe | .476 | .399 | .018 | .720 | 0.944 | | |
| SwTr | .227 | .576 | -.021 | .389 | .483 | 0.957 | |
| QIS | .358 | .186 | .073 | .347 | .282 | .183 | 0.944 |

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